INVERSE KINEMATIC ANALYSIS OF ARTICULATED FIGURES USING THE FUZZY SELF–ORGANIZING FEATURE MAP

MITCHEL SOLTYS AND TERRY HUNTSBERGER
Intelligent Systems Laboratory
Department of Computer Science
University of South Carolina

ABSTRACT:
The success of modern neural network approaches to control suggests that they might provide the best hope for significant advances in robotic control and dynamic simulation. This work investigates the use of a new fuzzy self-organizing feature map network architecture to solve the inverse kinematic problem for a human or robotic arm having seven degrees of freedom in three dimensions. The reference frame system ARM (**A**rticulated **R**evolute **M**otion) created for the articulated figure (Soltys, 1991) follows traditional control conventions and thus is suitable for robotic environments. We report the results of some three–dimensional experiments for a seven degrees of freedom articulated arm comparing the fuzzy self–organizing feature approach to the backpropagation network.

INTRODUCTION

There has recently been a number of studies into the possibility of using neural networks for solving the inverse kinematics problem in robotics. Josin, Charney and White, and independently Elsley, discuss using backpropagation to solve the inverse kinematic problem for a two–dimensional articulated figure having two degrees of freedom (Josin, Charney and White, 1988, and Elsley, 1988). Bruwer and Cruse (Bruwer and Cruse, 1990) use neural network architectures to solve the inverse kinematics problem for a three degrees of freedom two dimensional arm.

Caudill (Caudill, 1988) applies a Kohonen self–organizing net to an articulated figure problem similar to that in (Josin, Charney and White, 1988). Ritter, Martinetz and Schulten (Ritter, Martinetz, and Schulten, 1989) extend the Kohonen self–organizing network to establish a topology conserving map for learning kinematic and dynamic properties of a simulated robot arm.

The work presented in this paper describes the use of a new fuzzy self-organizing feature map network architecture (Huntsberger and Ajjimarangsee, 1990) for solving the inverse kinematics problem in articulated figure control. This study uses the ARM configuration which is suitable for a three-dimensional representation and practical kinematic implementation of a human or robotic arm having seven degrees of freedom (Soltys, 1991). In this model, specifications are given for medically observed joint angle limits with their corresponding representation in the Denavit and Hartenberg (D&H) notation (Denavit and Hartenberg, 1955), which is commonly used in modern robotic control.

The next section briefly describes the ARM system that was used to model human articulated figure motion for the purposes of training the neural networks. This is followed by a description of the fuzzy self-organizing feature map network. Finally, we present the results of some experimental studies comparing the fuzzy self-organizing and backpropagation networks applied to the inverse kinematics problem for a seven degrees of freedom arm.

THE ARM SYSTEM

The general description of a line in a reference frame using only four parameters d, a, θ, and α can be used in the D&H system to describe the unique positioning of a n degree of freedom robotic arm. We are assuming revolute joints, so the parameters d, a and α are fixed and the θ's for each joint will be referred to as the joint angles. A leading text on physical examinations used by medical students contains the ranges of motion in the joints of interest (Bates, 1987). While the angle specifications are exactly what we need to properly limit and model motion, they are not described in a manner which is particularly useful for either graphic simulation or robotic control. This led us to develop the ARM system, which maps the joint angles and limits into a representation suitable for robotic control. Figure 1 gives the joint angle limits, as well as their mapping into the ARM system.

The relative position and orientation in the D&H representation for each of the eight reference frames of the ARM system compared to that of a robotic arm are shown in Figure 2. The link parameters and the minimum, initial and maximum joint angles (θ) associated with each link are also shown. The orientations shown in Figure 2 are for the initial configuration of the arm at rest. In the ARM system there are three sets of frames having coincident origins [0,1,2], [3,4], [5,6], whereas in the robotic system reference frames 5 and 6 aren't necessarily coincident.

NEURAL NETWORKS

The number of successful applications of neural network architectures in recent literature shows that they are well suited to certain applications. Backpropagation is perhaps the most commonly used supervised learning algorithm (Rumelhart and McClelland, 1986). Kohonen's two layer self–organizing feature map is more of a classification network than a non–linear mapping network (Kohonen, 1984). The fuzzy self–organizing feature map (FSOFM) algorithm is described in (Huntsberger and Ajjimarangsee, 1990).

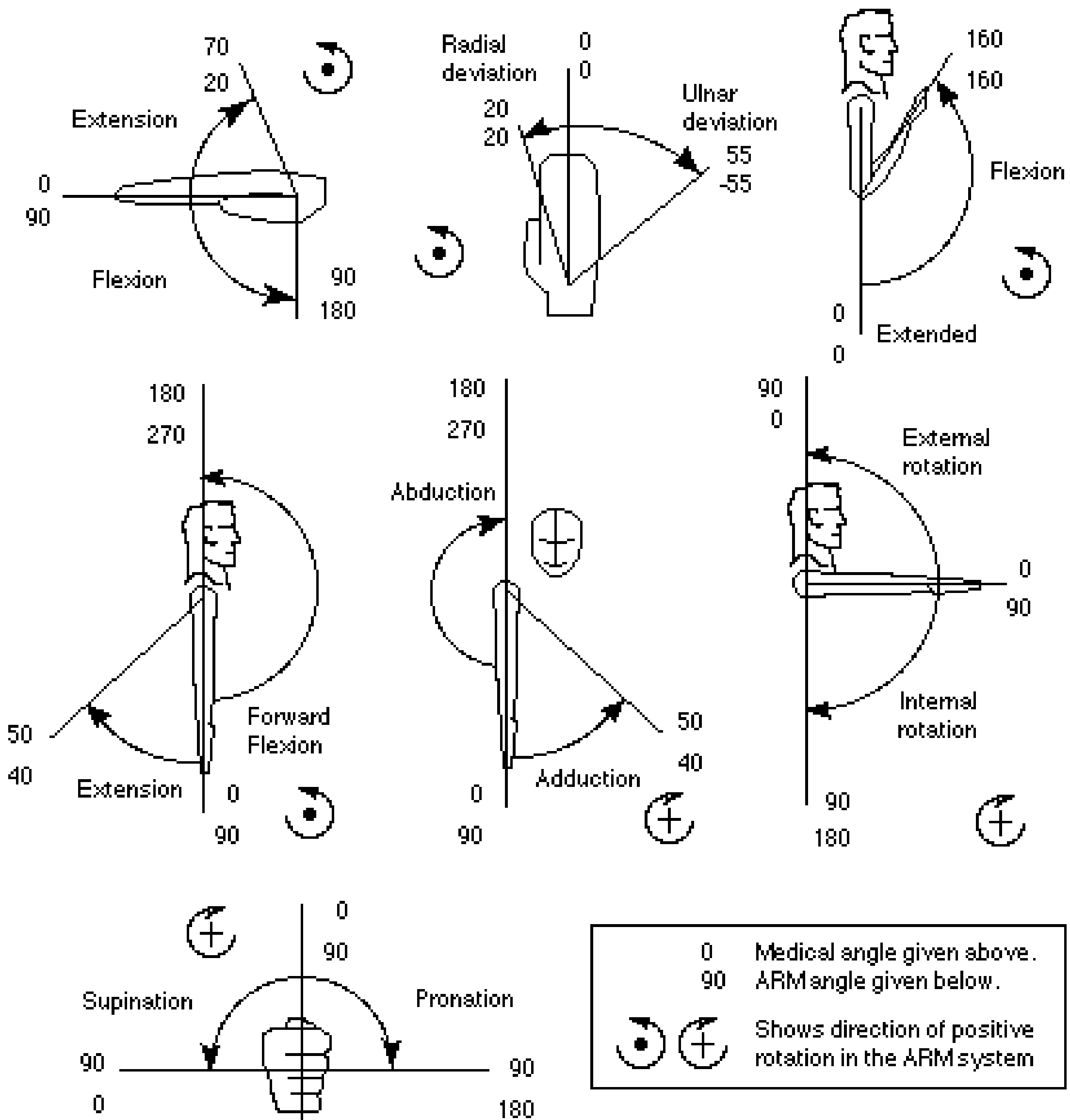
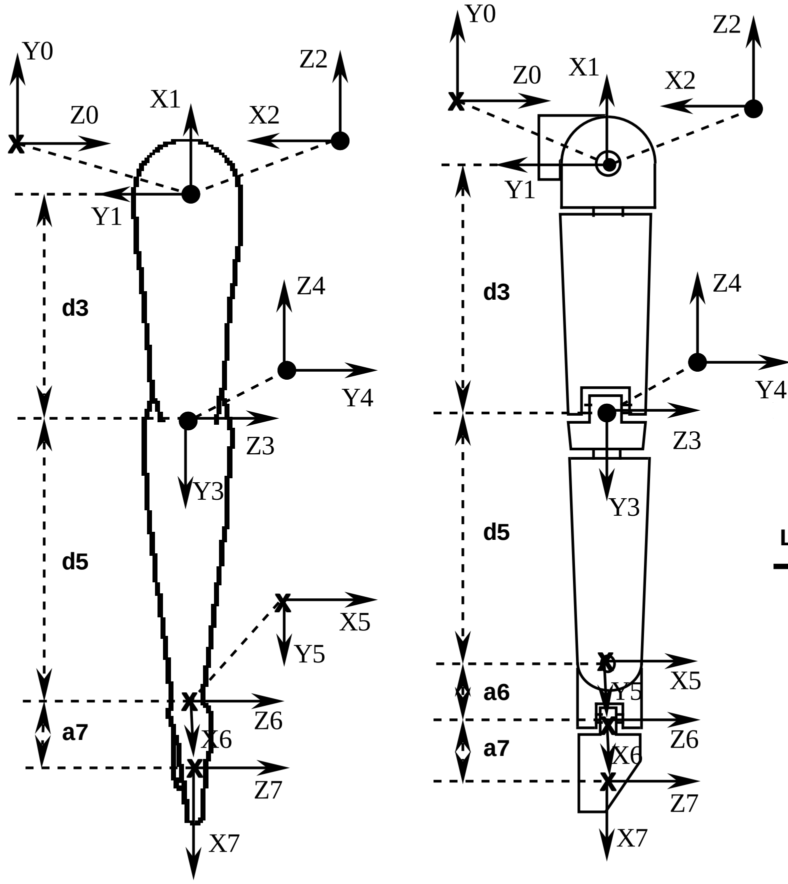


Figure 1: Angles and joint limitations in the ARM system.

EXPERIMENTAL STUDIES

In order to test the generalization capabilities of the networks, several motion paths were created. The networks were trained on 11 points evenly spaced along paths created using a forward kinematics program. The backpropagation network was trained with twelve hidden layer nodes. Two sets of data points representative of two separate motions were generated. The first motion, "bowling", is a motion representative of an arm swinging as it might do when rolling a bowling ball. The second motion, "push", is representative of a motion which might be used to push a lever in a fairly horizontal direction. Training was done on the basis of a single point (end–effector) position, or three points (elbow, wrist and end–effector) positions.



● axis out of plane
X axis into plane

Joint Angles

Link	θ_{min}	θ_{init}	θ_{max}
1	40	90	270
2	40	90	270
3	0	90	180
4	0	0	160
5	0	90	180
6	20	90	180
7	-55	0	20

Link Parameters

Link	θ	α	d	a
1	$\theta 1$	-90	0	0
2	$\theta 2$	90	0	0
3	$\theta 3$	-90	-Lua	0
4	$\theta 4$	90	0	0
5	$\theta 5$	-90	-Lla	0
6	$\theta 6$	90	0	Lw
7	$\theta 7$	0	0	Lh

Figure 2: Reference frames in ARM and robot systems.

Table 1 gives statistics for the generalization ability of the networks in terms of their error in the end–effector position and in the joint angle calculation. Max Dist is the maximum Euclidean distance error between the actual and desired end–effector positions and Max Diff is the maximum angle difference for any one angle for any of the generated points in the test motion path. The test cases are labeled by network type (b for backpropagation, f for FSOFM), motion path (b for bowling, p for push), and number of known arm points.

The "bowling" and "push" data sets, like most task motions, are comprised of configurations whose change in elbow position is proportional and related to the change in the end–effector position in a relatively non–redundant way. There is a substantial improvement in the overall learning accuracy for the backpropagation network in the use of three training points versus one training point. In none of the cases was there significant improvement for the FSOFM network by including additional known points. This is because the error does not arise from an inability to categorize the states, but from a failure to properly interpolate between known states. A membership value is given to an entire set of angles in a given state, thus in the current implementation there is no means to attribute different membership values for each of the angles in the arm.

TABLE 1: ERROR STATISTICS

Test Case	Max Dist	Rms Error	Avg Dist	Max Diff	Sq Error	Avg Diff
bb1	30.5456	85.2695	5.2370	-0.7201	8.0650	-0.0891
bb3	1.6992	0.1705	0.2601	0.0227	0.0084	0.0005
bp1	1.1382	0.0721	0.2050	-0.0269	0.0037	-0.0001
bp3	1.1598	0.1159	0.2577	-0.0256	0.0041	0.0000
fb1	6.3467	4.1557	1.3777	-0.0648	0.1169	-0.0284
fb3	5.4618	3.0570	1.2107	-0.0558	0.0893	-0.0212
fp1	1.0095	0.1584	0.3012	-0.0411	0.0399	0.0014
fp3	0.9972	0.1333	0.2793	-0.0362	0.0330	0.0010

Even with the additional training points, the back propagation network still took at least two orders of magnitude more iterations to converge than the FSOFM. Furthermore, the time for each iteration in the backpropagation network can be longer than that for the FSOFM net, depending on the number of hidden layer nodes. The FSOFM architecture is more suitable for real time learning, especially if the problem is decomposed into several portions having several small networks.

CONCLUSIONS

The majority of previous works which discuss neural network approaches to the inverse kinematics of articulated figures limit their studies to two degrees of freedom in a two dimensional plane. Our research has extended studies of neural network applications to three dimensions and seven degrees of freedom, demonstrating a successful initial application of fuzzy self-organizing feature map architecture to the non–linear inverse kinematic problem. The ARM system is the first system to provide a D&H representation for a human arm. Since the reference frame choices obey the convention of modern robotic control, it may be used with either neural network architectures or with traditional matrix methods. Finally, the ARM system accurately models medically observed human joint limitations.

This capability makes the model useful for studies of human factors modeling within environments (Woolford, Pandya, and Maida, 1990). The angle limits and rest angles are documented for all seven degrees of freedom. Joint angle limits were seen to be enforced as a result of training on valid ARM configurations. We are presently investigating an extension of the ARM system using a hierarchy of neural networks responsible for learning different aspects of the inverse kinematics. It should be possible, upon further study, to realize the primary function of each of the degrees of freedom and construct a new network seeking to model these functions. Other issues of interest include learning position as a function of incremental change verses absolute location, and establishing a means for a neural network to handle multiple correct solutions.

REFERENCES

Bates, B., (1987). *A Guide to Physical Examination and History Taking, 4th Ed*, J.B Lippencott Company, Phila, PA, 428–432.

Bruwer, M., Cruse, H., (1990). A network model for the control of the movement of a redundant manipulator, *Biological Cybernetics*, **62** (6), 549–555.

Caudill, M. (1988). Neural networks primer: Part IV, *AI Expert*, **3** (8), 61–67.

Denavit J., R. S. Hartenberg, R. S., (1955). A kinematic notation for lower–pair mechanisms based on matrices, *Journal of Applied Mechanics*, June, 215–221.

Elsley, R. K., (1988). A learning architecture for control based on back-propagation neural networks, *Proc. IEEE International Conference on Neural Networks, vol 2*, July, 587–594.

Huntsberger, T. L., Ajjimarangsee, P, (1990). Parallel self–organizing feature maps for unsupervised pattern recognition, *International Journal of General Systems*, **16**, 357–372; also reprinted in *Fuzzy Models for Pattern Recognition*, (Eds. J. C. Bezdek and S. K. Pal), IEEE Press, Piscataway, NJ, 83–495, 1992.

Josin, G., Charney, D., and White, D., (1988). Robot control using neural networks, *Proc. IEEE International Conference on Neural Networks, vol 2*, 625–631.

Kohonen, T., (1984). *Self-Organization and Associative Memory*, Springer-Verlag, Berlin.

Ritter, H. J., Martinetz, T. M., and Schulten, K. J., (1989). Topology–conserving maps for learning visuo-motor-coordination, *Neural Networks*, **2**, 159–168.

Rumelhart, D. E., McClelland, J. L., (1986). *Parallel Distributed Processing.* MIT Press, Cambridge, MA.

Soltys, M., (1991). Neural network solutions to the inverse kinematics problem, M.S. Thesis, Department of Computer Science, University of South Carolina.

Woolford, B., Pandya, A., and Maida, J., (1990). Development of biomechanical models for human factors evaluations, *Space Operations Applications and Research* **2**, 552–556.